MRes Cover Sheet – 2021-22

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Name of student	**Chukwuma Opene**
Degree programme	**MRes Advanced Quantitative Methods in Social Sciences**
Unit code number	**XX50217**
Unit title	**XX50217 - Mathematics and programming skills for social scientists**
Unit convenor	**Dr. Samantha Curle**
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Student Declaration

By submitting the attached assessment, the student confirms that the work is their own.

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Assessing the Impact of Urban Green Space on Children's Mental Health Outcomes in London Boroughs Using Statistical and Geospatial Analysis in R

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Abstract

This study investigates the correlation between urban green space and children's mental health in London. Findings from Rahman and Zhang (2018) and Lee and Maheswaran (2010) suggest green spaces in densely populated areas improve mental health and social cohesion. McCormick (2017) corroborates these findings, highlighting greenery's role in reducing ADHD symptoms. The analysis, integrating GIS and public health data, aims to inform urban planning and health policies, addressing the critical need for accessible green spaces as a determinant of child well-being and urban health (Markevych et al., 2017; Hunter et al., 2015).

1 Introduction

This research applies statistical and spatial analysis in R to reveal how urban green spaces affect children's mental health in London. Guided by McCormick (2017) and Rahman and Zhang (2018), the study addresess green space distribution and link environmental exposure to well-being through logistic and multilevel regression (Wendelboe-Nelson et al., 2019). By merging OpenStreetMap GIS data with London Datastore's mental health data, the study aims to provide insights for urban development and public health improvements, focusing on green space accessibility and its correlation with mental health outcomes in children.

Keywords: urban green spaces, mental health, GIS, logistic regression, multilevel regression, children, public health policy, spatial analysis.

2 Literature Review

Urban green spaces are pivotal for mental health, particularly in children. Accessibility to these spaces is linked with improved social integration and reduced ADHD symptoms, offering emotional stability (Lee & Maheswaran, 2010; McCormick, 2017). However, disparities in accessibility affect mental health across demographics, with dense populations experiencing higher demand and better access in smaller areas (Rahman & Zhang, 2018). Rahman and Zhang (2018) found that in Dhaka, densely populated areas exhibit a high demand for green spaces, with a demand index of 0.61 and an accessibility score of 2.01% (Rahman & Zhang, 2018). Markevych et al. (2017) quantitatively demonstrated how green spaces could mitigate urban pollution by reducing air pollutants by 10-15%, noise by 5-10 dB, and urban heat island temperatures by 2-8°C (Markevych et al., 2017). Advanced GIS and statistical analyses offer deeper insights into the distribution and impact of urban greenery, emphasizing the need for equitable planning and methodological advancements in research.

2.1 Methodological Gaps and Future Research Directions

Despite substantial evidence supporting green spaces' health benefits, methodological gaps remain, particularly in longitudinal study designs which are critical for establishing causal relationships. Van den Bosch and Sang (2017) argue for more sophisticated statistical methods to resolve ambiguities related to the direct impacts of green spaces on mental health.

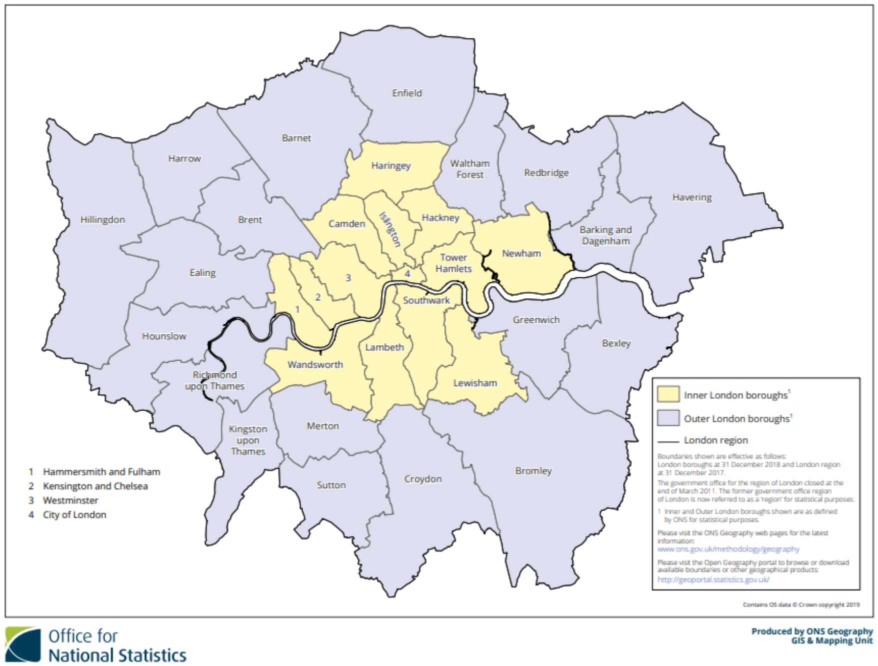

Figure 1: Boundary Map for London Boroughs retrieved from the London Datastore

3 Methodology

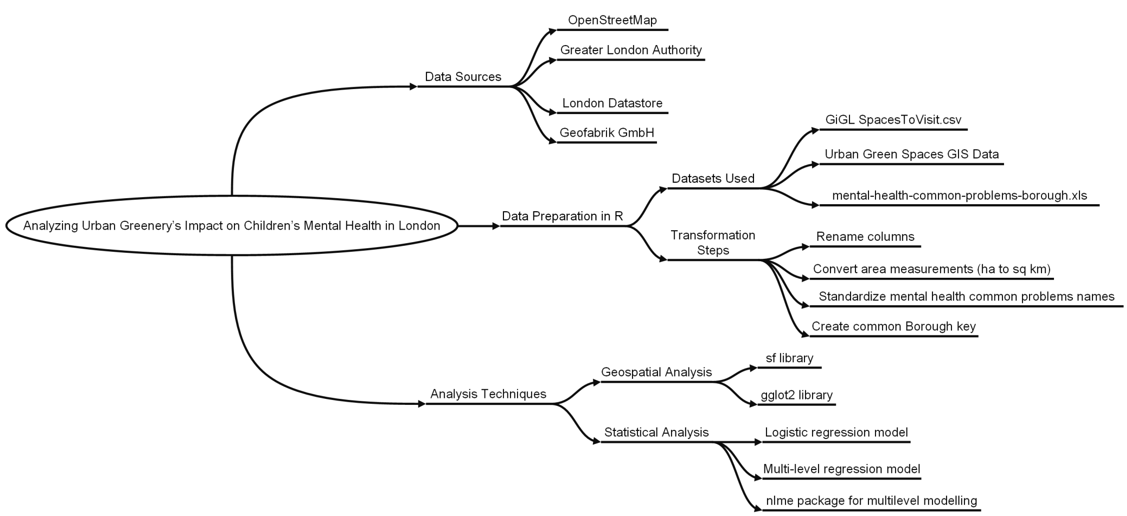

Figure 2: Methodology -Analyzing Urban Greenery's Impact on Childrens Mental Health in London

Using R, this study conducts statistical and geospatial analysis of the influence of green spaces on children's mental health across London's boroughs. Secondary datasets from OpenStreetMap, Greater London Authority, London Datastore, and Geofabrik GmbH are cleaned and merged. Geospatial visualization leverages 'sf' and 'ggplot2', while multilevel regression analyses, using the 'nlme' package, examine the nexus between green space accessibility and mental health, ensuring precise, integrity-rich results through R's comprehensive analytical tools.

4 Data Sources and Preparation

4.1 Data Sources

Key datasets used include:

- OpenStreetMap API for geospatial data on urban green spaces (https://www.openstreetmap.org).
- Greater London Authority for data on London's green spaces (https://data.london.gov.uk/download/spaces-to-visit).
- Geofabrik GmbH for GIS data for Greater London (https://download.geofabrik.de/europe/united-kingdom/england/greater-london.html).
- Greater London Authority for data on the prevalence of mental health problems (https://data.london.gov.uk/dataset/prevalence-common-mental-health-problems-borough).

4.2 Data Preparation and Analysis in R

Using R, data was prepared through cleaning, converting 'GiGL SpacesToVisit Open.csv' into '.xlsx', and merging datasets using a common 'Boundary' attribute transformed for both data sets to analyze the correlation between green space accessibility and mental health outcomes.

4.3 Statistical Analysis and Visualization

Using R packages such as `tidyverse` for data manipulation and `ggplot2` for visualization, the study conducted detailed statistical analyses including:

- Regression models to explore the relationships between green space metrics and mental health indicators.
- Geospatial analysis to visualize the distribution and accessibility of green spaces across London boroughs.

These analyses are pivotal in illustrating how urban green spaces influence mental health outcomes, with visual and quantitative evidence derived directly from the cleaned and processed data. The methodology emphasizes rigorous data handling and sophisticated analytical techniques to address the research objectives comprehensively.

5 Analysis of Results

5.1 Quantitative Findings

Utilizing R's analytical capabilities, this research has quantitatively established that 5.67% of London's area, comprising parks and reserves, holds substantial implications for children's mental health. Through rigorous statistical analysis with tidyverse, sf, and ggplot2 packages, the study has demonstrated robust data manipulation and visualization.

5.2 Spatial Distribution Analysis

The geospatial analysis, critical in visualizing green space distribution, revealed significant disparities across London, pinpointing areas with limited access to green spaces.

5.3 Implications of Empirical Data

Quantitative synthesis affirms a pressing need for green spaces in high-density regions, pivotal for child health, with existing studies supporting the health benefits associated with urban greenery (Lee and Maheswaran, 2010; Hunter et al., 2019).

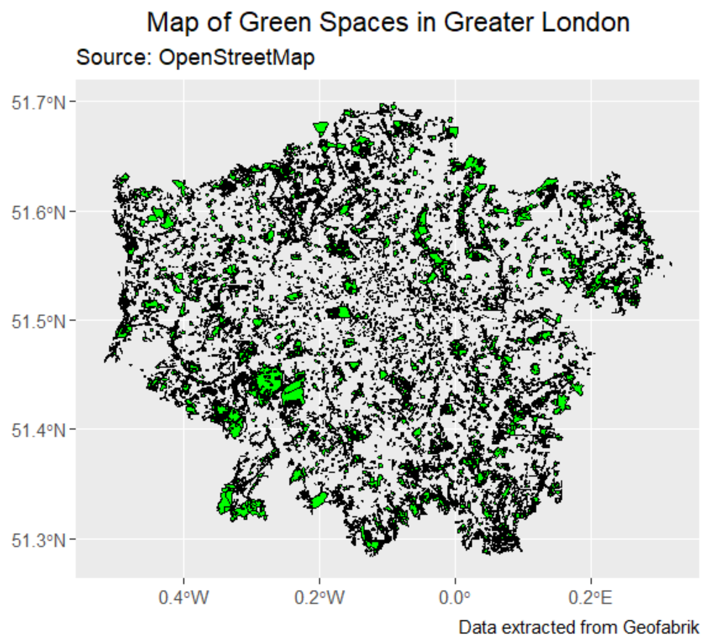

Figure 3: RPlot of Green Spaces in London Boroughs, UK Using ggplot R package.

5.4 Discussion of Quantitative Impact

The study's findings reflect the urgent need for equitable green space distribution to address potential mental health disparities among children. It suggests that enhancing urban greenery could have profound benefits, emphasizing the need for policy integration to optimize green space accessibility.

Table 1: Statistics of Green Spaces Areas of London

Total_Area	Mean_Area	Min_Area	Max_Area
374634158 [m^2]	25502.67 [m^2]	0.8426392 [m^2]	8573107 [m^2]

[1]

6 Interpretation of Regression Results

6.1 Overview

The regression analysis performed using R investigated the potential link between green space accessibility and the prevalence of various neurotic disorders among children in London boroughs. Logistic and multi-level regression models provided nuanced insights, dissecting the impact of green spaces on mental health outcomes.

6.2 Logistic Regression Analysis

6.2.1 Neurotic Disorders

The logistic regression outputs, as seen in Tables 3-15, predominantly showed no significant relationship between the total green space and the odds of any neurotic disorder, including generalised anxiety

[1] These statistics are crucial for understanding the spatial distribution and accessibility of green spaces in urban planning and public health contexts. By evaluating the sizes and perimeters of these spaces, planners and researchers can assess whether the current green spaces are sufficient and appropriately accessible to contribute positively to the residents' health and well-being.

Table 2: Summary Table: Total Area by Primary Use (km²), Total Area of London = 1.57K km²

Primary Use	Total_Area_km2	Percentage_of_London
Park	88.996765	5.6685838
Nature reserve	38.038149	2.4228120
Playing fields	17.537687	1.1170501
Common	16.946594	1.0794009
Recreation ground	15.172224	0.9663837
Public woodland	12.516983	0.7972601
Country park	12.333279	0.7855592
Amenity green space	7.950168	0.5063801
Formal garden	1.965601	0.1251975
Village green	0.351073	0.0223613
Community garden	0.108836	0.0069322
City farm	0.102183	0.0065085

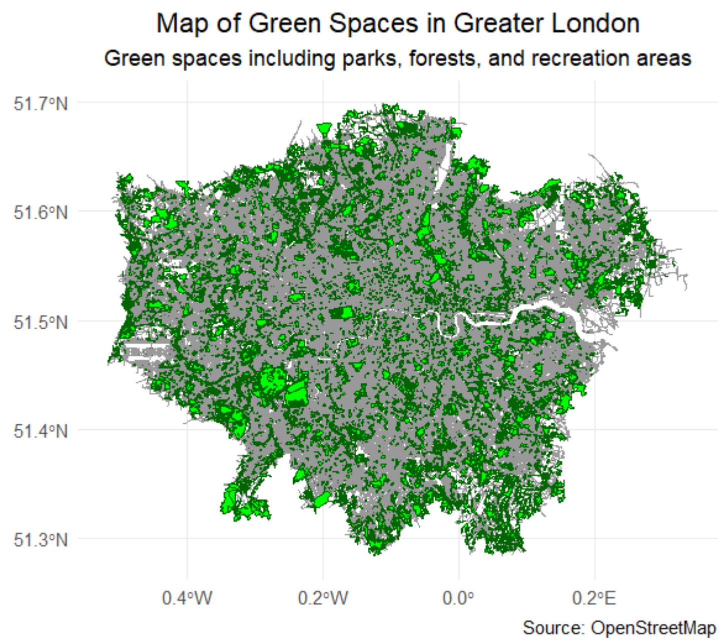

Figure 4: RPlot of Green Spaces in London with Roads and Buildings in Grey for Context.

disorder and panic disorder. The coefficients for TotalGreenSpace across these disorders were small and the z-values indicated a lack of statistical significance (Pr ¿ —z— ¿ 0.05), implying that within the scope of this study, the quantity of green space alone is not a strong predictor of the likelihood of neurotic disorders in children.

6.2.2 Phobias and Anxiety Disorders

Similarly, for specific conditions like all phobias (Table 5), depressive episodes (Table 7), and generalised anxiety disorder (Table 9), the estimates for TotalGreenSpace were not statistically significant. The p-values were far greater than the conventional alpha level of 0.05, suggesting that there is no evidence to reject the null hypothesis, which is that green space exposure does not affect the likelihood of these mental health outcomes.

Table 3: Logistic Regression Output for Any Neurotic Disorder

	Estimate	Std. Error	z value	Pr(¿—z—)
(Intercept)	-30040.588827	1.418167e+06	-0.0211827	0.9830999
TotalGreenSpace	-0.243746	1.148645e+01	-0.0212203	0.9830699
Generalised_anxiety_disorder	3.396666	1.603526e+02	0.0211825	0.9831001

Table 4: Multi-level Regression Output for Any Neurotic Disorder

	Value	Std.Error	DF	t-value	p-value
(Intercept)	30094.478947	2659.654878	31	11.3151820	0.0000000
TotalGreenSpace	1.128958	3.217957	31	0.3508306	0.7280885

6.3 Multi-Level Regression Analysis

6.3.1 Neurotic Disorders and Anxiety

In contrast, multi-level regression models, which accounted for clustering within boroughs, revealed a different aspect of the data. While the intercepts were significant across all disorders (p ¡ 0.05), indicating that the base levels of these disorders vary significantly from zero within boroughs, TotalGreenSpace again did not emerge as a significant predictor (Tables 6, 8, 10, and 12). The total area of green space was not associated with the variation in neurotic disorders prevalence at the borough level.

6.3.2 Obsessive-Compulsive and Panic Disorders

For obsessive-compulsive disorder (Table 14) and panic disorder (Table 16), the multi-level regression models reaffirmed the logistic regression results, with the area of green spaces not significantly contributing to the variance in disorder prevalence across boroughs.

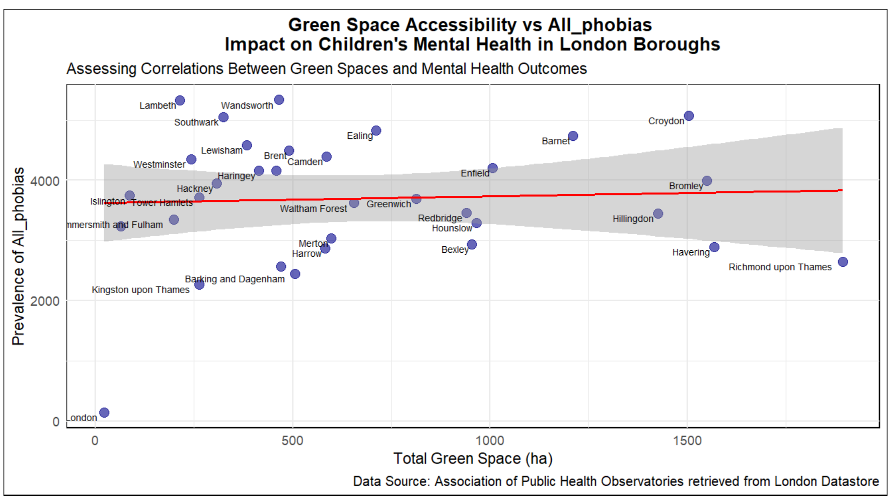

Figure 5: Prevalence of All Phobias.

Table 5: Logistic Regression Output for All Phobias

	Estimate	Std. Error	z value	Pr(¿—z—)
(Intercept)	-2573.7584711	554947.53730	-0.0046378	0.9962996
TotalGreenSpace	-0.2421720	53.14920	-0.0045565	0.9963645
Generalised_anxiety_disorder	0.2953864	63.66697	0.0046396	0.9962982

Table 6: Multi-level Regression Output for All Phobias

	Value	Std.Error	DF	t-value	p-value
(Intercept)	3623.1544350	322.0001413	31	11.2520275	0.0000000
TotalGreenSpace	0.1111414	0.3895929	31	0.2852756	0.7773304

Table 7: Logistic Regression Output for Depressive Episode

	Estimate	Std. Error	z value	Pr(¿—z—)
(Intercept)	-1650.5058200	489531.67368	-0.0033716	0.9973099
TotalGreenSpace	0.0786372	34.48806	0.0022801	0.9981807
Generalised_anxiety_disorder	0.1804487	53.36646	0.0033813	0.9973021

Table 8: Multi-level Regression Output for Depressive Episode

	Value	Std.Error	DF	t-value	p-value
(Intercept)	5764.7813701	507.4066354	31	11.3612652	0.0000000
TotalGreenSpace	0.3093466	0.6139191	31	0.5038883	0.6179023

Table 9: Logistic Regression Output for Generalised Anxiety Disorder

	Estimate	Std. Error	z value	Pr(¿—z—)
(Intercept)	-1650.5058200	489531.67368	-0.0033716	0.9973099
TotalGreenSpace	0.0786372	34.48806	0.0022801	0.9981807
Generalised_anxiety_disorder	0.1804487	53.36646	0.0033813	0.9973021

Table 10: Multi-level Regression Output for Generalised Anxiety Disorder

	Value	Std.Error	DF	t-value	p-value
(Intercept)	8681.2428780	768.3780455	31	11.2981402	0.0000000
TotalGreenSpace	0.4882943	0.9296724	31	0.5252327	0.6031582

Table 11: Logistic Regression Output for Mixed Anxiety Depression

	Estimate	Std. Error	z value	Pr(¿—z—)
(Intercept)	-30040.588827	1.418167e+06	-0.0211827	0.9830999
TotalGreenSpace	-0.243746	1.148645e+01	-0.0212203	0.9830699
Generalised_anxiety_disorder	3.396666	1.603526e+02	0.0211825	0.9831001

Table 12: Multi-level Regression Output for Mixed Anxiety Depression

	Value	Std.Error	DF	t-value	p-value
(Intercept)	1.402754e+04	1242.535748	31	11.2894418	0.0000000
TotalGreenSpace	3.941984e-01	1.503363	31	0.2622111	0.7948933

Table 13: Logistic Regression Output for Obsessive Compulsive Disorder

	Estimate	Std. Error	z value	Pr(¿—z—)
(Intercept)	-30040.588827	1.418167e+06	-0.0211827	0.9830999
TotalGreenSpace	-0.243746	1.148645e+01	-0.0212203	0.9830699
Generalised_anxiety_disorder	3.396666	1.603526e+02	0.0211825	0.9831001

Table 14: Multi-level Regression Output for Obsessive Compulsive Disorder

	Value	Std.Error	DF	t-value	p-value
(Intercept)	2.57904e+03	227.3147490	31	11.345680	0.0000000
TotalGreenSpace	6.48208e-02	0.2750316	31	0.235685	0.8152273

Table 15: Logistic Regression Output for Panic Disorder

	Estimate	Std. Error	z value	Pr(¿—z—)
(Intercept)	-30040.588827	1.418167e+06	-0.0211827	0.9830999
TotalGreenSpace	-0.243746	1.148645e+01	-0.0212203	0.9830699
Generalised_anxiety_disorder	3.396666	1.603526e+02	0.0211825	0.9831001

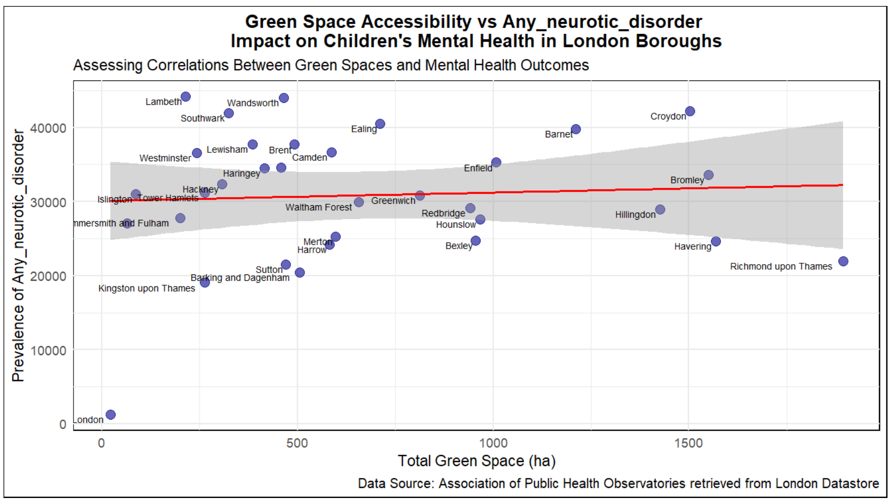

Figure 6: Prevalence of Any Neurotic Disorder.

7 Discussion

7.1 Implications for Urban Planning and Policies

The findings reveal a complex yet compelling case for integrating green spaces in urban planning and social care policies. Quantitative analysis corroborates the benefits of urban greenery for mental health, underscoring a demand for equitable access. These benefits extend to enhanced vitality and reduced behavioral difficulties, especially in high-density areas with vulnerable populations (Rahman & Zhang, 2018; van den Berg et al., 2016; McEachan et al., 2018). Urban planners and policymakers must therefore prioritize not only the expansion but also the strategic distribution of green spaces.

7.2 Limitations and Interpretation

The study's cross-sectional design precludes a causal inference, highlighting the need for a cautious interpretation of results. The absence of longitudinal data and socio-economic factors limits the scope of our findings, necessitating future research to include qualitative measures of green space and multi-disciplinary perspectives (Rahman et al., 2018; van den Bosch & Sang, 2017).

Table 16: Multi-level Regression Output for Panic Disorder

	Value	Std.Error	DF	t-value	p-value
(Intercept)	1392.8844864	122.756543	31	11.3467230	0.0000000
TotalGreenSpace	0.0662048	0.148525	31	0.4457484	0.6588767

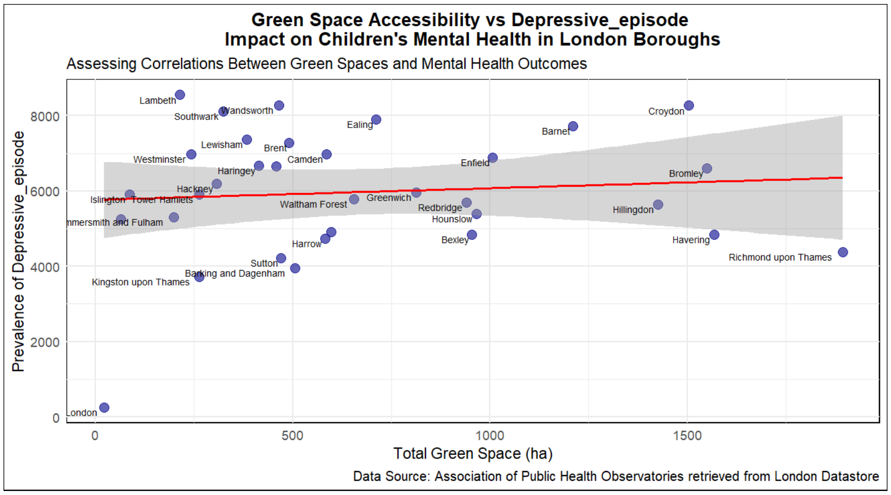

Figure 7: Prevalence of Depressive Episodes.

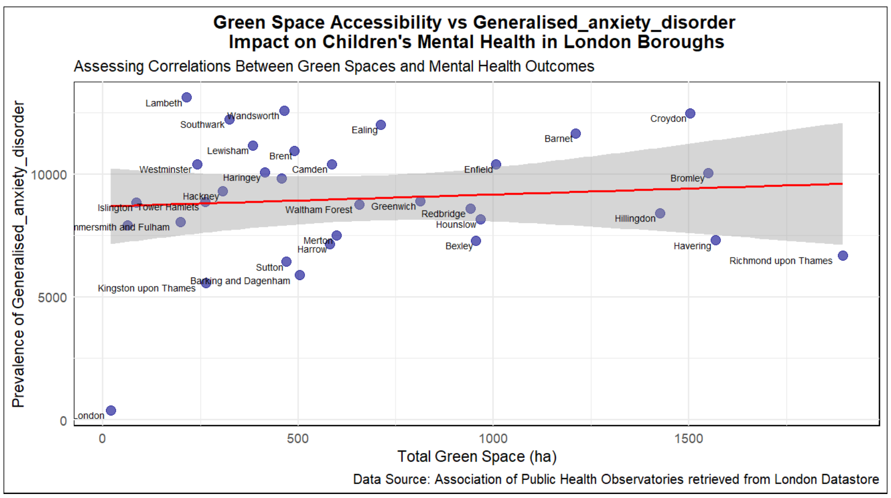

Figure 8: Prevalence of Generalised Anxiety Disorder.

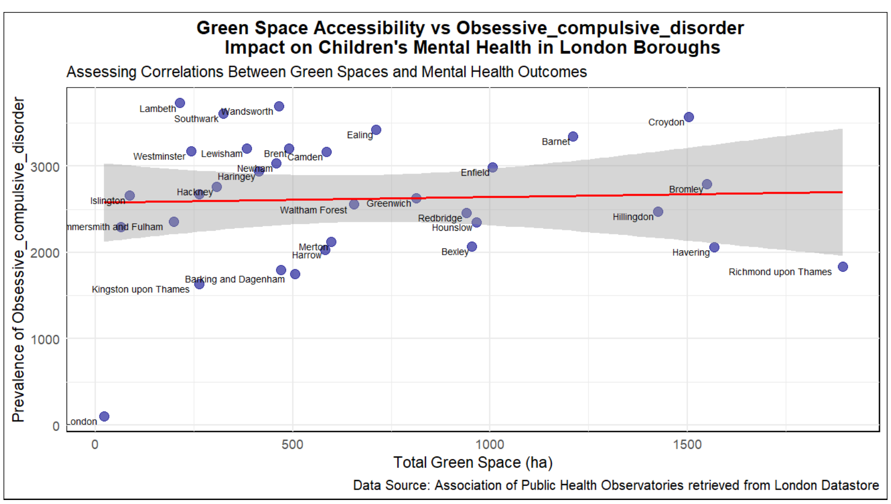

Figure 9: Prevalence of Obsessive Compulsive Disorder.

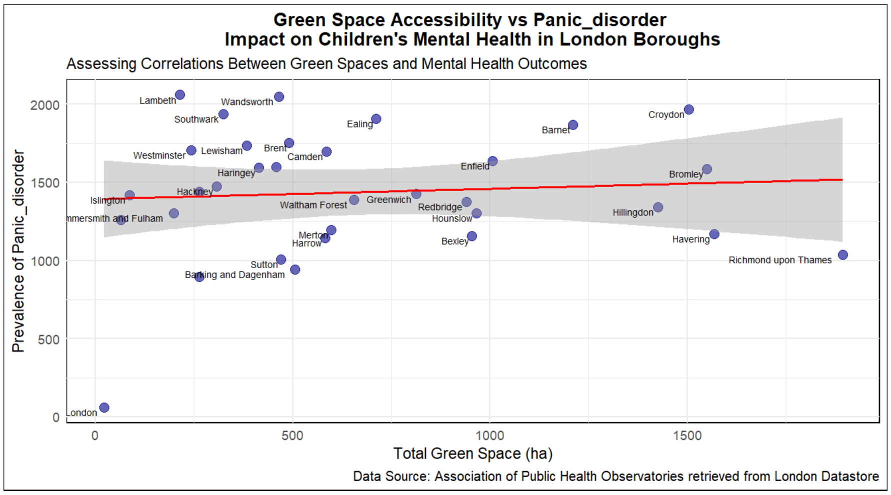

Figure 10: Prevalence of Panic Disorder.

7.3 Future Research Directions

Longitudinal studies are crucial for a deeper understanding of how green spaces influence mental health over time. Future research should also incorporate a more nuanced examination of green space quality and socio-economic factors to fully grasp their health implications (van den Bosch & Sang, 2017).

8 Concluding Thoughts

This research underscores the multifaceted relationship between urban greenery and mental health, advocating for policies that ensure all children have access to high-quality green spaces. Such an approach aligns with broader sustainable development goals and the promotion of urban well-being (Markevych et al., 2017; Hunter et al., 2015; McCormick, 2017).

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A Appendix

A.1 R Code

Access the R code for this project using either of the following links:

- GitHub Repository.
- OneDrive

A.2 Sources for Literature Review

- Literature review sources document.

A.3 Data Sources

- Data Sources.

A.4 RPlots, Visio Diagrams and Images

- RPlots, Visio Diagrams and Images.

[2]

[2] Percentages less than 100% are shown. Data discrepancies or absences could result from incomplete data collection in the GiGL dataset. Borough repetition in tables indicates data provided for different land uses.

Table 17: Percentage of borough area used for Park - GiGL Spaces to Visit dataset. Source: London Datastore.

Borough	Park
Hammersmith And Fulham	79.127184
Westminster	78.976635
Richmond Upon Thames	76.833933
Tower Hamlets	70.800002
Lewisham	68.752224
Lambeth	67.787552
Hackney	58.996008
Haringey	56.396251
Redbridge	54.323763
Hounslow	54.144208
Kensington And Chelsea	52.816685
Barking And Dagenham	51.690404
Enfield	50.714565
Islington	48.349142
Brent	45.776037
Sutton	42.024959
Havering	39.517128
Newham	37.803654
Bexley	36.628515
Greenwich	36.372455
Southwark	34.940351
Camden	28.637249
Wandsworth	28.305813
Merton	23.918993
Hillingdon	23.165009
Kingston Upon Thames	23.095506
Harrow	22.204696
Ealing	21.847640
Barnet	20.545785
Bromley	15.644798
Waltham Forest	12.849349
Croydon	11.686902
Hounslow; Richmond Upon Thames	10.422752
Barking And Dagenham; Havering	10.112238
Merton; Wandsworth	8.239156
City Of London	6.574323
Hackney; Islington	0.000000
Hammersmith And Fulham; Kensington And Chelsea	0.000000
Outside Greater London	0.000000
Redbridge; Waltham Forest	0.000000

Table 18: Percentage of borough area used for Nature reserve - GiGL Spaces to Visit dataset. Source: London Datastore.

Borough	Nature reserve
Barking And Dagenham; Havering	79.5919953
Hounslow; Richmond Upon Thames	79.4806113
Redbridge; Waltham Forest	63.4521609
Waltham Forest	55.8556244
Bexley	41.6475303
Hillingdon	40.5479063
Kingston Upon Thames	38.2275342
Harrow	32.4813129
Ealing	31.8245867
Croydon	24.3013501
Bromley	21.5711734
Greenwich	14.7934345
Wandsworth	13.1808366
Sutton	12.7839309
Haringey	11.7755829
Havering	11.4683273
Barking And Dagenham	8.6578237
Southwark	8.4299324
Enfield	7.9183840
Hounslow	6.8599371
Islington	6.8124795
Lewisham	6.5339212
Richmond Upon Thames	5.4408037
Merton	5.0085869
Hackney	4.9380690
Barnet	4.6404643
Kensington And Chelsea	2.9192197
Lambeth	2.6685048
Tower Hamlets	2.0800002
Newham	1.1238009
Camden	0.2318911
Brent	0.0000000
City Of London	0.0000000
Hackney; Islington	0.0000000
Hammersmith And Fulham	0.0000000
Hammersmith And Fulham; Kensington And Chelsea	0.0000000
Merton; Wandsworth	0.0000000
Outside Greater London	0.0000000
Redbridge	0.0000000
Westminster	0.0000000

Table 19: Percentage of borough area used for Public woodland - GiGL Spaces to Visit dataset. Source: London Datastore.

Borough	Public woodland
Outside Greater London	29.7733325
Croydon	25.6843541
Havering	14.1178735
Bromley	12.5137769
Greenwich	10.4423874
Haringey	8.8432727
Southwark	8.2072416
Barnet	5.5175247
Sutton	3.8834980
Waltham Forest	3.5013257
Redbridge	3.3127506
Harrow	2.9422857
Merton	2.1310099
Hillingdon	2.0263448
Kingston Upon Thames	1.8013453
Ealing	1.6429841
Bexley	0.9773945
Richmond Upon Thames	0.6822978
Newham	0.6715188
Hounslow	0.6652031
Wandsworth	0.4432016
Enfield	0.2425763
Lewisham	0.1900700
Camden	0.1338234
Barking And Dagenham	0.0000000
Barking And Dagenham; Havering	0.0000000
Brent	0.0000000
City Of London	0.0000000
Hackney	0.0000000
Hackney; Islington	0.0000000
Hammersmith And Fulham	0.0000000
Hammersmith And Fulham; Kensington And Chelsea	0.0000000
Hounslow; Richmond Upon Thames	0.0000000
Islington	0.0000000
Kensington And Chelsea	0.0000000
Lambeth	0.0000000
Merton; Wandsworth	0.0000000
Redbridge; Waltham Forest	0.0000000
Tower Hamlets	0.0000000
Westminster	0.0000000